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Classification of Paroxysmal Atrial Fibrillation using Second Order System

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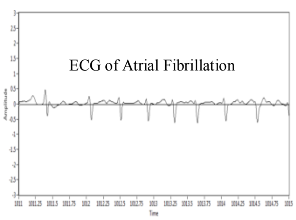
Graphical abstract



Abstract

In this paper, we monitored and analyzed the characteristics of atrial fibrillation in patient using second order approach. Atrial fibrillation is a type of atria arrhythmias, disturbing the normal heart rhythm between the atria and lower ventricles of the heart. Heart disease and hypertension increase risk of stroke from atrial fibrillation. This study used electrocardiogram (ECG) signals from Physiobank, namely MIT-BIH Atrial Fibrillation Dataset and MIT-BIH Normal Sinus Rhythm Dataset. In total, 865 episodes for each type of ECG signal were classified, specifically normal sinus rhythm (NSR) of human without arrhythmia, normal sinus rhythm of atrial fibrillation patient (N) and atrial fibrillation (AF). Extracted parameters (forcing input, natural frequency and damping coefficient) from second order system were characterized and analyzed. Their ratios, time derivatives, and differential derivatives were also observed. Altogether, 12 parameters were extracted and analysed from the approach. The results show significant difference between the three ECGs of forcing input, and derivative of forcing input. Overall system performance gives specificity and sensitivity of 84.9 % and 85.5 %, respectively.

Keywords: Atrial fibrillation; normal sinus rhythm; hypertension; stroke; electrocardiogram; second order system

Abstrak

Dalam kajian ini, kami mengawasi dan menganalisis sifat-sifat dan ramalan tercetusnya fibrilasi atrium pada pesakit. Fibrilasi atrium adalah sejenis aritmia atria, yang mengganggu degupan normal jantung antara atria dan ventrikal bawah. Penyakit jantung dan hipertensi meningkatkan risiko strok daripada fibrilasi atrium. Kajian ini menggunakan isyarat elektrokardiogram (ECG) dari Physiobank, bernama MIT-BIH Atrial Fibrillation Dataset dan MIT-BIH Normal Sinus Rhythm Dataset. Sejumlah 865 episod bagi setiap pengekelasan isyarat ECG, dengan lebih spesifik, irama sinus yang normal (NSR) manusia tanpa aritmia, irama sinus yang normal pesakit fibrilasi atrium (N) dan irama fibrilasi atrium pesakit (AF). Parameter yang diekstrak (masukan paksaan, frekuensi natural, pekali kelembapan) dari sistem peringkat kedua dicirikan dan dianalisa. Nisbahnya, terbitan masa, dan pembezaan terbitan juga diperhatikan di mana keseluruhannya terdapat 12 parameter yang dianalisis. Hasil menunjukkan perbezaan yang signifikan antara masukan paksaan, dan terbitan masukan paksaan. Keseluruhan persembahan sistem memberikan kekhususan dan kepekaan masing-masing, 84.9 % dan 85.5 %.

Kata kunci: Fibrilasi atrium; irama sinus yang normal; hipertensi; strok; elektrokardiogram; sistem peringkat kedua

1.0 INTRODUCTION

Atrial fibrillation is one of atria arrhythmias which can life threaten if not diagnose earlier by physician or doctor. It is a condition where heart fibrillates when electrical impulses disorganize and the contraction of atrias become disorganize. During atria muscle fibrillation, atria can no longer pumps blood to ventricles. Therefore, ventricles contract rapidly. Normal rhythm between the atria and ventricles of the heart are disturb and may cause someone to suffer heart attack, high blood pressure, coronary heart disease or heart valve disease.[1] Normal human can show symptoms of feeling lightheaded, out of breath, week, heart racing or unevenly beating heart.[1] Normal heart rate maintains at 60 beats per minute during rest and can fire rapidly between 180-200 beats per minute while exercising.[2] In atria fibrillation, heart can fire up to 600 beats per minute with ventricular rate in the region of more than 100 pulses per minute.[1-2] The loss of atrial contraction can leads to formation of blood clots in the heart as blood in the atria become stagnate. It can enlarge and moving to brain which resulting as ischemic stroke in patient. Stroke is number three killer in Malaysia after diabetes and cancer,[3] and has been the third leading cause of death in most countries around the world for a very long time.[4] Therefore this study concern was on characterizing the normal and atrial fibrillation ECG signal using second order system to classify atrial fibrillation signal in-between normal heart rhythm (normal sinus rhythm or normal heart beat).

1.1 Previous Research

A few existing algorithms are performed to detect, differentiate and classify atrial fibrillation ECG signal with other signal. Previous research are based on P-wave absence[5-7] or relied on RR intervals[8-12] or combinations of both[13-14] to detect atrial fibrillation. Methods such as neural networks[15], wavelet analysis[16-17], and QRST cancellation[18-19] were investigated and developed. While semantic mining approach was developed in gaming[20] and pattern recognition for estimating opponent strategy[21] and detecting ventricular arrhythmias.[22-24]

In one of the previous research, the P wave absence was found in 34 of 68 stroke patients which developed atrial fibrillation (AF) and other were classified as non-AF contraction with the number of 88.2% and 37.3% of AF in each group.[5]

Another researcher developed a sequential analysis of the atrial activity in a single ECG lead for automatic detection of atrial flutter and atrial fibrillation.[7] The approached used P wave absence and ventricular arrhythmia detection which achieved accuracy and sensitivity of 98.8% and 95.7% respectively.[7]

Meanwhile another had developed algorithm for atrial fibrillation detection based on RR interval time series that achieved sensitivity of 94.1% and specificity of 95.1%.[8] The dataset used were MIT-BIH Atrial Fibrillation Database and MIT-BIH Arrhythmia Database. The combination of both databases gave sensitivity of 90.2% and specificity of 91.2% in the study.

Another study that detects atrial fibrillation based on RR-interval, data from MIT-BIH Atrial Database were used.[10] The estimation between standard density histograms and a test density histogram by the Kolmogorov-Smirnov (KS) test gave significant difference. The average sensitivity and average specificity achieved were 93.2% and 96.7% respectively.[10]

M. Stridh and M. Rosenqvist performed RR-interval and separated RR intervals between disturbances or occasional ectopic beats from irregular rhythms.[13] Later, P-wave detection was performed and achieved sinus rhythm cases of 93% and atrial fibrillation cases of 98% successfully recognized from the database. In addition, P. De Chazal and C. Heneghan also used RR-interval and P wave shape in automated assessment of the ECG for predicting the onset of atrial fibrillation.[14] Results show that features based on RR intervals were most successful with score of 41/50.

In another study, the classification performance of normal sinus rhythm and atrial fibrillation ECGs using neural network gave high accuracy.[15] The trained 3-layer network achieved 100% accuracy of 24 and 28 normal sinus rhythm and atrial fibrillation state ECGs respectively.[15]

None of the above study had use second order dynamic approach. First of its kind, the same approach had been use to characterize ventricular tachycardia and ventricular fibrillation, namely semantic mining.[22-24] The paper mentioned that semantic mining able to recognize and differentiate between ventricular tachycardia, ventricular fibrillation and normal heart rhythm. Based on that, this study extends the usage of second order system for atrial fibrillation classification. The second order system applied to atrial fibrillation dataset was described in our initial study.[25]

2.0 EXPERIMENTAL

2.1 Data Collection

Data collection from Physiobank, namely MIT-BIH Atrial Fibrillation Dataset and MIT-BIH Normal Sinus Rhythm Dataset were used.[26] This study used sample number #04126 and #16265 from the datasets respectively. The data was in binary format of 12-bit resolution, with range of ±10 mV. The sampling frequency are 250 Hz and 128 Hz respectively, while typical bandwidth recording of approximately 0.1 Hz to 40 Hz. The ECG signals were windowed into 4 seconds episodes, and overlapped by 3 seconds (moving filter). Matlab software was used to convert the binary data obtained from Physiobank to ascii format as LabVIEW software compatible format. All processing were done in LabVIEW platform.

2.2 Data Processing

Butterworth band pass filter was used. The transfers function as in (1). Pass band of 1 to 30 Hz was chosen. LabVIEW software was used in this study.

$$H(z) = \frac{0.027+0.109z^{-1}+0.164z^{-2}+0.109z^{-3}+0.027z^{-4}}{1-2.791z^{-1}+4.327z^{-2}-2.791z^{-3}+z^{-4}} \quad (1)$$

2.3 Extraction Of Parameters

The second order system is described as equation (2).

$$\omega^{-2}.x'' + 2\zeta\omega^{-1}x' + x = \mu\,;\ x(0) = x_0\ ;\ x'(0) = x'_0 \quad (2)$$

where ω is the natural frequency, ζ is the damping coefficient and μ is the forcing input of the system. These three parameters are extracted from the ECG signal to characterize its characteristic for further analysis and study.

By differentiating (2) with respect to t (3) and divide it with x'' (4), damping coefficient, ζ can be obtained and differentiate with respect to t another time (5) to obtain natural frequency, ω.

$$\omega^{-2}.x''' + 2\zeta\omega^{-1}x'' + x' = 0 \quad (3)$$

$$\frac{\omega^{-2}.x'''}{x''} + \frac{2\zeta\omega^{-1}x''}{x''} + \frac{x'}{x''} = 0 \quad (4)$$

$$\frac{\omega^{-2}(x''.x''' - x'''.x'')}{(x'')^2} + 0 + \frac{x''.x'' - x'.x'''}{(x'')^2} = 0 \quad (5)$$

From (4)

$$\zeta = -\left[\frac{\omega^{-2}.x''' + x'}{2\omega^{-1}.x''}\right] \quad (6)$$

From (5)

$$\omega^2 = \frac{x''.x''' - (x''')^2}{x'.x''' - (x'')^2} \quad (7)$$

While forcing input, μ is obtained from (2).

$$\mu = \omega^{-2}.x'' + 2\zeta\omega^{-1}x' + x \quad (8)$$

The parameters obtained from second order system (damping coefficient, ζ; natural frequency, ω; and forcing input, μ) are monitored, as well as:

i. the ratio (ratios of forcing input to natural frequency, μ/ω; ratios of forcing input to damping coefficient, μ/ζ; ratios of natural frequency to damping coefficient, ω/ζ),
ii. differential of time (the derivative of the natural frequency with respect to time, $d\omega/dt$; the derivative of the damping coefficient with respect to time, $d\zeta/dt$; the derivative of the forcing input with respect to time, $d\mu/dt$), and
iii. derivatives of differential (the derivative of the forcing input with respect to the natural frequency, $d\mu/d\omega$; the derivative of the forcing input with respect to the damping coefficient, $d\mu/d\zeta$; and the derivative of the natural frequency with respect to the damping coefficient, $d\omega/d\zeta$) to provide a realistic different in analyzing the features. In total, twelve parameters were analyzed. Results are show and discuss in results and discussion.

Figure 1 shows overall workflow for this study. Sample from MIT-BIH Normal Sinus Rhythm Database was rescaled into 250 Hz, to be analyzed with 250 Hz sample of MIT-BIH Atrial Fibrillation Database.

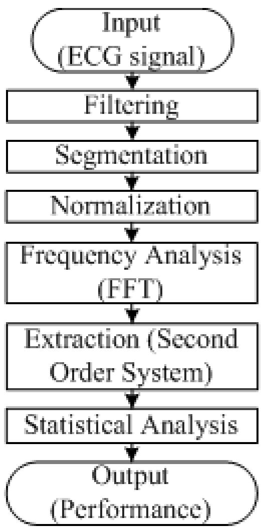


Figure 1 The workflow of the study

3.0 RESULTS

The results observed during this study, includes, the scaling of sample of MIT-BIH Normal Sinus Rhythm Dataset from 128 Hz to 250 Hz, the filtering process, segmentation into specific episode, normalization, transforming a function of time into frequency using fast-Fourier Transform (FFT), extraction of features using second order system, beneficial of statistical t-test for classification, and also the performance observation. In this results section, four parts are reveals as follow.

3.1 Scaling (From 128 Hz to 250 Hz)

In order to have same frequency sampling of samples used, sample from MIT-BIH Normal Sinus Rhythm Dataset was rescale from 128 Hz to 250 Hz, to meet the sampling frequency of MIT-BIH Atrial Fibrillation Dataset for convenient and easy to analyze. Figure 2 shows the example of sample number #16265 of 128 Hz and 250 Hz.

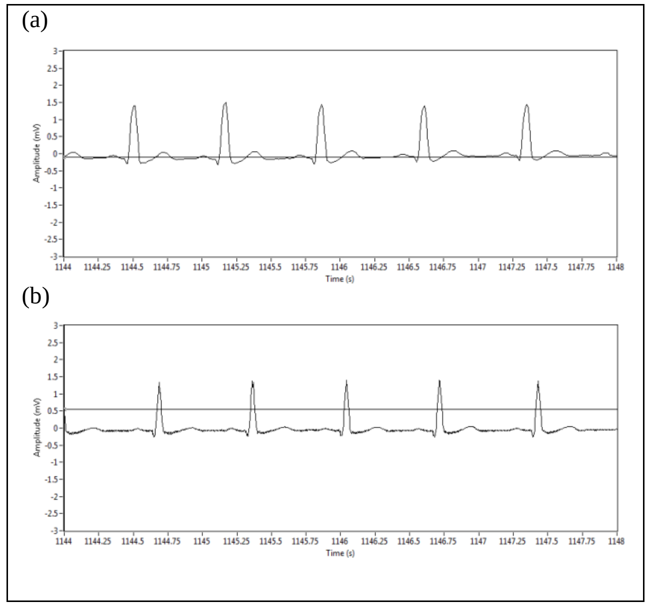


Figure 2 Rescaling of 128 Hz (a) to 250 Hz (b) of MIT-BIH Normal Sinus Rhythm Dataset

3.2 Three Types Of Electrocardiogram

Figure 3 shows the three types of electrocardiogram (ECG) used in the study. Figure 3(a) shows the ECG of normal sinus rhythm of heathy human, Figure 3(b) shows the ECG of normal sinus rhythm of human with atrial fibrillation, while Figure 3(c) shows the ECG of atrial fibrillation taken from the same patient of Figure 3(b). The figure of 4 seconds is the segmentation for an episode of ECG to be processed each time (Figure 3).

The ECGs of normal sinus rhythm and atrial fibrillation were chosen based on the period that sequentially occurred in the sample. Therefore, for sample number #04126, of 10 hours ECG recording, it was stated in Physiobank that atrial fibrillation had happened seventh time.[26] The length of sequentially occurred ECG of normal sinus rhythm and atrial fibrillation were analyzed. Thus, providing 865 episodes for each type of ECGs. As well as sample number #16265 of normal human, 865 episodes were analyzed. Both leads (Lead I and Lead II) were analyzed for those three types of ECG. The processing was done in LabVIEW version 11.0.

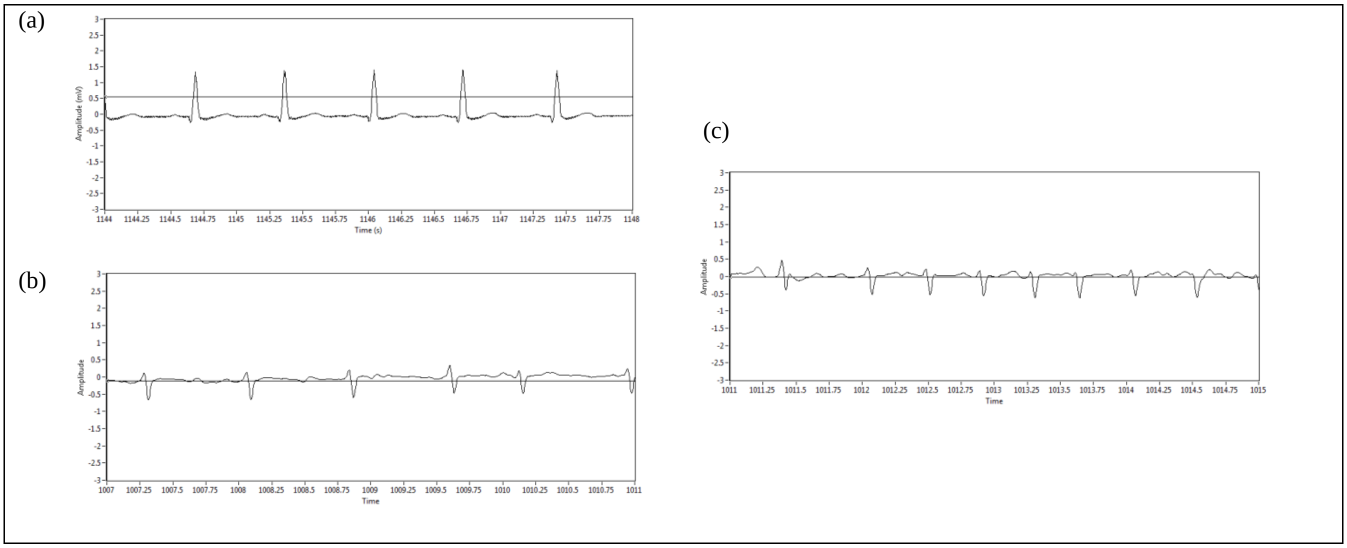


Figure 3 Three types of ECG (a) Normal ECG of healthy human, (b) Normal ECG of human having atrial fibrillation, (c) ECG of atrial fibrillation

3.3 Extraction Of Parameters And Statistical Analysis

Table 1 and Table 2 show the average (Av) and standard deviation (Sd) of normal human ECG (NSR), normal sinus rhythm of atrial fibrillation patient's ECG (N) and atrial fibrillation ECG (AF), for lead I and lead II respectively. Furthermore, the statistical two-tailed t-test was performed for both leads, and the results show in Table 3 and Table 4, respectively. Analysis of the result is shown in section 4.0.

3.4 Performance

Figure 4 and Figure 5 show two extraction parameters, which are forcing input, μ; ratios of forcing input to natural frequency, μ/ω; the derivative of the forcing input with respect to time, dμ/dt; and the derivative of the forcing input with respect to the natural frequency, dμ/dω, respectively, for Lead 1 of the three types of ECGs in the study, i.e. normal human ECG (NSR), normal sinus rhythm of atrial fibrillation patient's ECG (N) and atrial fibrillation ECG (AF).

The result of the performance test is summarized in Table 5. The true positive rate (sensitivity, Se) is for unhealthy human ECG's features which correctly identified as having sick, while the true negative rate (specificity, Sp) for healthy human ECG's features that correctly identified as not having sick.

4.0 ANALYSIS AND DISCUSSIONS

The study aims at classifying paroxysmal atrial fibrillation using second order system. Therefore, the ECGs chosen were normal sinus rhythm of healthy human (NSR), normal sinus rhythm of patient suffers atrial fibrillation (N), and atrial fibrillation of respective human (AF). The MIT-BIH databases were used in the study (NSR dataset and AF dataset). According to MIT-BIH AF Dataset, the ECG recorded for 10 hours, and the selected sample during this study, sample number #04126, had suffered AF for seven times along the ECG trace. The optimum time that can be used were 865 episodes for AF and N, which had occurred sequentially during the seven time of AF recorded. Two ECG Leads (Lead I and Lead II) were provided from each dataset. Both Leads were used for three types of ECG aforementioned. As a result, 5190 episodes were analyzed($865\ episodes \times 3\ ECGs \times 2\ Leads$), where each episode is four seconds in length.

The MIT-BIH NSR Dataset was provided in different sampling frequency (128 Hz) compared to MIT-BIH AF Dataset. Therefore, the rescaling process was done, up-sampling the sampling frequency into 250 Hz, as MIT-BIH AF Dataset sampling frequency. After that, the ECGs were filtered, segmented, normalized, transformed, extracted, analyzed and observed.

The features of the three types of ECG (NSR, N and AF), were extracted using second order system, the concept of dynamics. Twelve features were observed, i.e. damping coefficient, ζ; natural frequency, ω; and forcing input, μ; ratios of forcing input to natural frequency, μ/ω; ratios of forcing input to damping coefficient, μ/ζ; ratios of natural frequency to damping coefficient, ω/ζ; the derivative of the natural frequency with respect to time, dω/dt; the derivative of the damping coefficient with respect to time, dζ/dt; the derivative of the forcing input with respect to time, dμ/dt; the derivative of the forcing input with respect to the natural frequency, dμ/dω; the derivative of the forcing input with respect to the damping coefficient, dμ/dζ; and the derivative of the natural frequency with respect to the damping coefficient, dω/dζ. Table 1 and Table 2 show the parameters averaged values. Both Leads (Lead I and Lead II) had increment in the averaged values from NSR-to-N-to-AF for six parameters, i.e. natural frequency, ω; and forcing input, μ; ratios of forcing input to natural frequency, μ/ω; the derivative of the natural frequency with respect to time, dω/dt; the derivative of the forcing input with respect to time, dμ/dt and the derivative of the forcing input with respect to the natural frequency, dμ/dω. Example for natural frequency, ω, the averaged valued are (NSR-to-N-to-AF) 0.9015-0.9104-0.9407 for Lead I, and 0.9237-0.9538-0.9601 for Lead II. Lead II provide higher value than Lead I. According to [22], the forcing input, μ of patient suffering ventricular arrhythmia, were averaged at 3.748±0.319 (Lead II), while current study found that μ of patient suffering atrial arrhythmia were averaged at 4.1609±2.4930 (Lead I) and 4.9446±2.5949 (Lead II), that were much greater than previous study. This could be that previous study[22], classified the ventricular arrhythmia according to natural frequency, ω, while current study according to forcing input, μ, which is more suitable for the samples under observation.

Statistical two-tailed t-test was done to examine the significant difference. Three group of examined were, i.e. NSR and N, NSR and AF, and, N and AF, for both Lead I and Lead II. As summarized in Table 3, it was found that forcing input, μ, and forcing input differential of time, dμ/dt, of Lead I ECGs gave significant differences for the three group aforementioned, with probability, p less than 0.0001 ($p < 0.0001$). Another two parameters, ratios of forcing input to natural frequency, μ/ω, and the derivative of the forcing input with respect to the natural frequency, dμ/dω, provided significant difference with $p < 0.001$, for the three group observed. While for Lead II (Table 4), there were significant differences with $p < 0.0001$, but only between two groups, i.e. NSR and N, and, NSR and AF, of natural frequency,ω. No significant differences found for the same parameter of the different groups.

Therefore, only two parameters can be considered to classify NSR, N and AF of Lead I ECG. The parameters are forcing input, μ, and the derivative of the forcing input with respect to time, dμ/dt. The sensitivity (Se) and specificity (Sp) of the classification system were summarized in Table 5. The true positive rate (Se) is for unhealthy human's ECG, that is AF signals, which correctly classified as having sick, whereas the true negative rate (Sp) is for healthy human's ECG, that is NSR signals, which correctly classified as not having sick. From the average data of the samples, the threshold for forcing input, μ, and the derivative of the forcing input with respect to time, dμ/dt, were set to 3.9996 and 0.9999, respectively. As a result, the specificity and sensitivity for the classification process were 84.9 % and 85.5 %, correspondingly, the same for both parameters (μ and dμ/dt). According to Figure 4 and Figure 5, in depth look can be seen for 100 samples of NSR and N each, and 100 samples of N and AF, for parameter μ and dμ/dt, correspondingly. Forcing input, μ of NSR tabulated in the range of 3-4 mV, while N and AF had wider range, from 0 to 10 mV. In comparison, normal heart rate beats at 60 bpm, while patient suffer from AF can feel heart beat of 100 to 600 per minute.[1-2]

5.0 CONCLUSION

In conclusion, of all twelve parameters, two parameters give significant difference for normal sinus rhythm of healthy person, normal sinus rhythm of patient suffering atrial fibrillation and atrial fibrillation, classification. Therefore, these two parameters (forcing input, μ and the differential of time of forcing input, dμ/dt) can be further studied to characterize and classify other samples among world population. Hybrid second order system approach may also be considered to increase the performance.

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Table 1 Average and standard deviation for lead I ECGs

Type		Parameter											
		ω	ζ	μ	μ/ω	μ/ζ	ω/ζ	dω/dt	dζ/dt	dμ/dt	dμ/dω	dμ/dζ	dω/dζ
NSR	Av	0.9015	-0.0003	3.7691	4.1864	-33000	-7531	0.2254	-0.0001	0.9423	4.1864	-33000	-7531
	Sd	0.0281	0.0004	0.3159	0.3845	303131	66837	0.0070	0.0001	0.0790	0.3845	303131	66837
N	Av	0.9104	0.0282	4.1609	4.8496	2019	368	0.2276	0.0071	1.0402	4.8496	2019	368
	Sd	0.1464	0.8689	2.4930	3.8110	167266	40229	0.0366	0.2172	0.6233	3.8110	167266	40229
AF	Av	0.9407	-0.0107	5.0500	5.4581	8019	1451	0.2352	-0.0027	1.2625	5.4581	8019	1451
	Sd	0.0999	0.1430	1.7013	2.2597	279598	56431	0.0250	0.0358	0.4253	2.2597	279598	56431

Table 2 Average and standard deviation for lead II ECGs

Type		Parameter											
		ω	ζ	μ	μ/ω	μ/ζ	ω/ζ	dω/dt	dζ/dt	dμ/dt	dμ/dω	dμ/dζ	dω/dζ
NSR	Av	0.9237	0.0006	4.6717	5.0514	-19695	-3645	0.2309	0.0001	1.1679	5.0514	-19695	-3645
	Sd	0.0308	0.0187	1.0200	1.0474	248025	39585	0.0077	0.0047	0.2550	1.0474	248025	39585
N	Av	0.9538	-0.0002	4.9446	5.1907	-5179	-230	0.2384	0.0000	1.2362	5.1907	-5179	-230
	Sd	0.0334	0.0119	2.5949	2.7543	263927	55209	0.0084	0.0030	0.6487	2.7543	263927	55209
AF	Av	0.9601	-0.0079	5.7085	5.9987	-6635	-1256	0.2400	-0.0020	1.4271	5.9987	-6635	-1256
	Sd	0.0529	0.1865	3.4696	3.7988	116734	19389	0.0132	0.0466	0.8674	3.7988	116734	19389

Table 3 t-test for lead I ECGs

Type	Parameter											
	ω	ζ	μ	μ/ω	μ/ζ	ω/ζ	dω/dt	dζ/dt	dμ/dt	dμ/dω	dμ/dζ	dω/dζ
(NSR, N)	0.0809	0.3351	**0.0000***	**0.0000***	0.0028	0.0029	0.0809	0.3351	**0.0000***	**0.0000***	0.0028	0.0029
(NSR, AF)	**0.0000***	0.0327	**0.0000***	**0.0000***	0.0035	0.0026	**0.0000***	0.0327	**0.0000***	**0.0000***	0.0035	0.0026
(N, AF)	**0.0000***	0.1941	**0.0000***	0.0001'	0.5872	0.6445	**0.0000***	0.1941	**0.0000***	0.0001'	0.5872	0.6445

' = $p < 0.001$

* = $p < 0.0001$

Table 4 t-test for lead II ECGs

Type	Parameter											
	ω	ζ	μ	μ/ω	μ/ζ	ω/ζ	dω/dt	dζ/dt	dμ/dt	dμ/dω	dμ/dζ	dω/dζ
(NSR, N)	**0.0000***	0.3138	0.0046	0.1691	0.2393	0.1401	**0.0000***	0.3138	0.0046	0.1691	0.2393	0.1401
(NSR, AF)	**0.0000***	0.1846	**0.0000***	**0.0000***	0.1641	0.1138	**0.0000***	0.1846	**0.0000***	**0.0000***	0.1641	0.1138
(N, AF)	0.0025	0.2255	**0.0000***	0.8819	0.6050	0.0025	0.2255	**0.0000***	**0.0000***	0.8819	0.6050	**0.0000***

* = $p < 0.0001$

Table 5 Performance test for ECG lead I

(AF, NSR)	Threshold	Positive (AF)		Negative (NSR)		Specificity (%) $\left\{Sp = \frac{TN}{TN+FP}\right\}$	Sensitivity (%) $\left\{Se = \frac{TP}{TP+FN}\right\}$
		True	False	False	True		
μ	3.9996	740	125	131	734	84.9	85.5
dμ/dt	0.9999	740	125	131	734	84.9	85.5

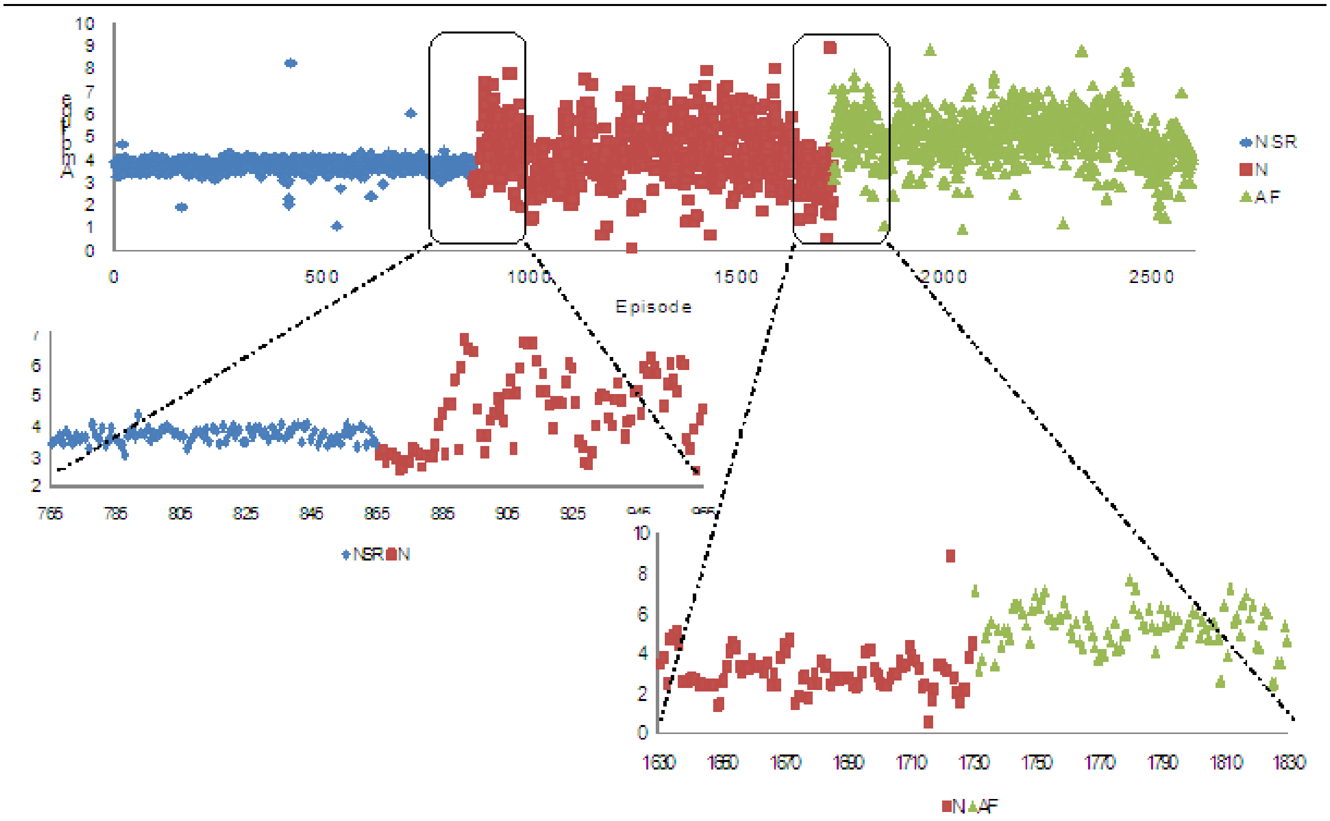

Figure 4 The forcing input, μ

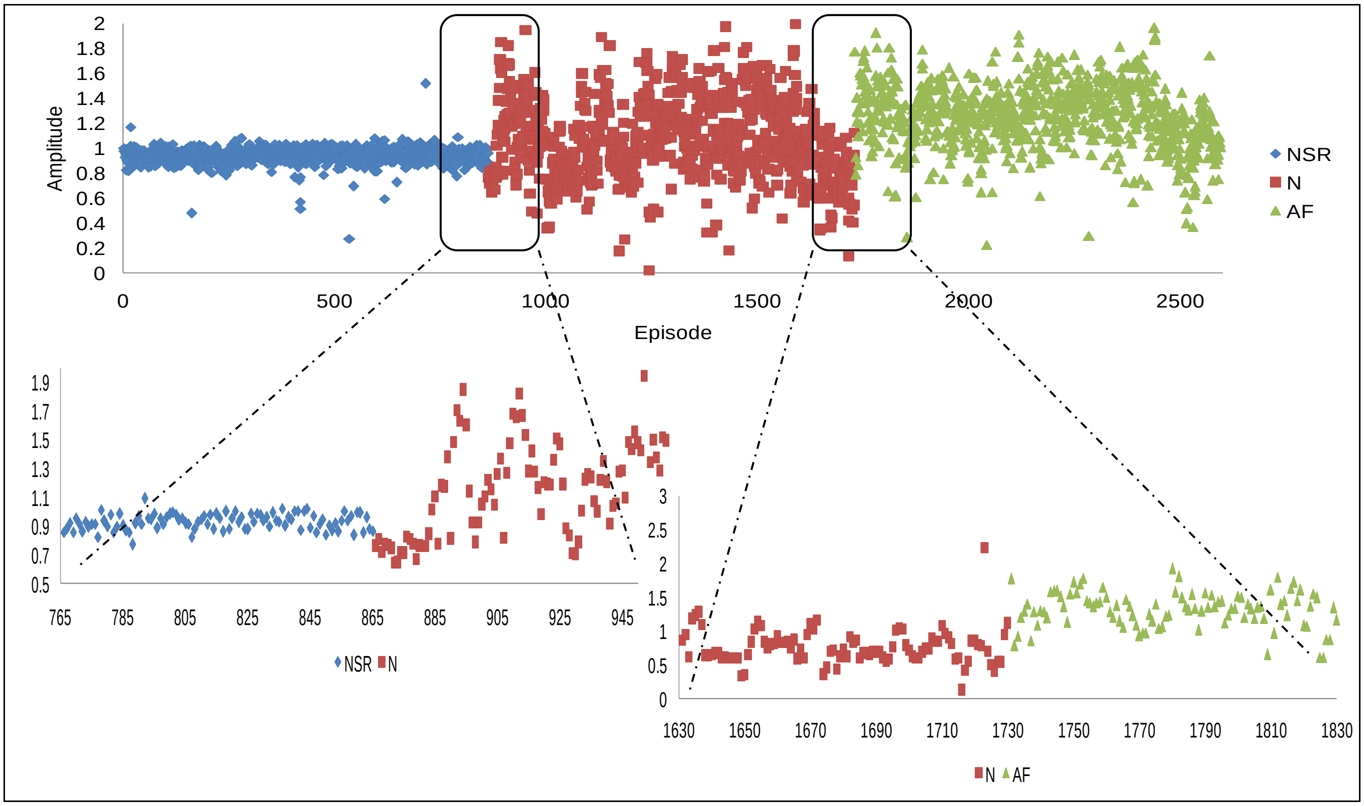

Figure 5 The derivative of the forcing input with respect to time, dμ/dt

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